

Optimizing Sales Force Effort

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Overview

- ◆ The general marketing/sales problem
- ◆ Why the focus on the pharmaceutical industry?
- ◆ Does sales force effort influence physician prescription behavior?
- ◆ Implications for sales managers
- ◆ The role of customer relationship management
- ◆ Conclusion
- ◆ Presentation based on my work with colleagues Peter Rossi, Pradeep Chintagunta and Sridhar Narayanan

The Standard Problem

Consider the generic sales response model:

$$y_{it} = f(x_{it} | \beta_i)$$

Unit of aggregation i
(account, store, territory,
customer)

Response Parameters

The diagram shows the equation $y_{it} = f(x_{it} | \beta_i)$ with two arrows pointing to it. One arrow points from the text 'Unit of aggregation i (account, store, territory, customer)' to the subscript i in both y_{it} and β_i . The other arrow points from the text 'Response Parameters' to the β_i term in the denominator of the function.

Inference focuses on conditional model: $y | x$

What is Our Contribution?

First, we can estimate response parameters for each *individual* customer

Second, we know that sales managers are smart. So, it is likely that X values are set with partial knowledge of response parameters?

If we don't account for this, then

- there will be a “bias” in the response parameters
- information in X about parameters unexploited in conditional model

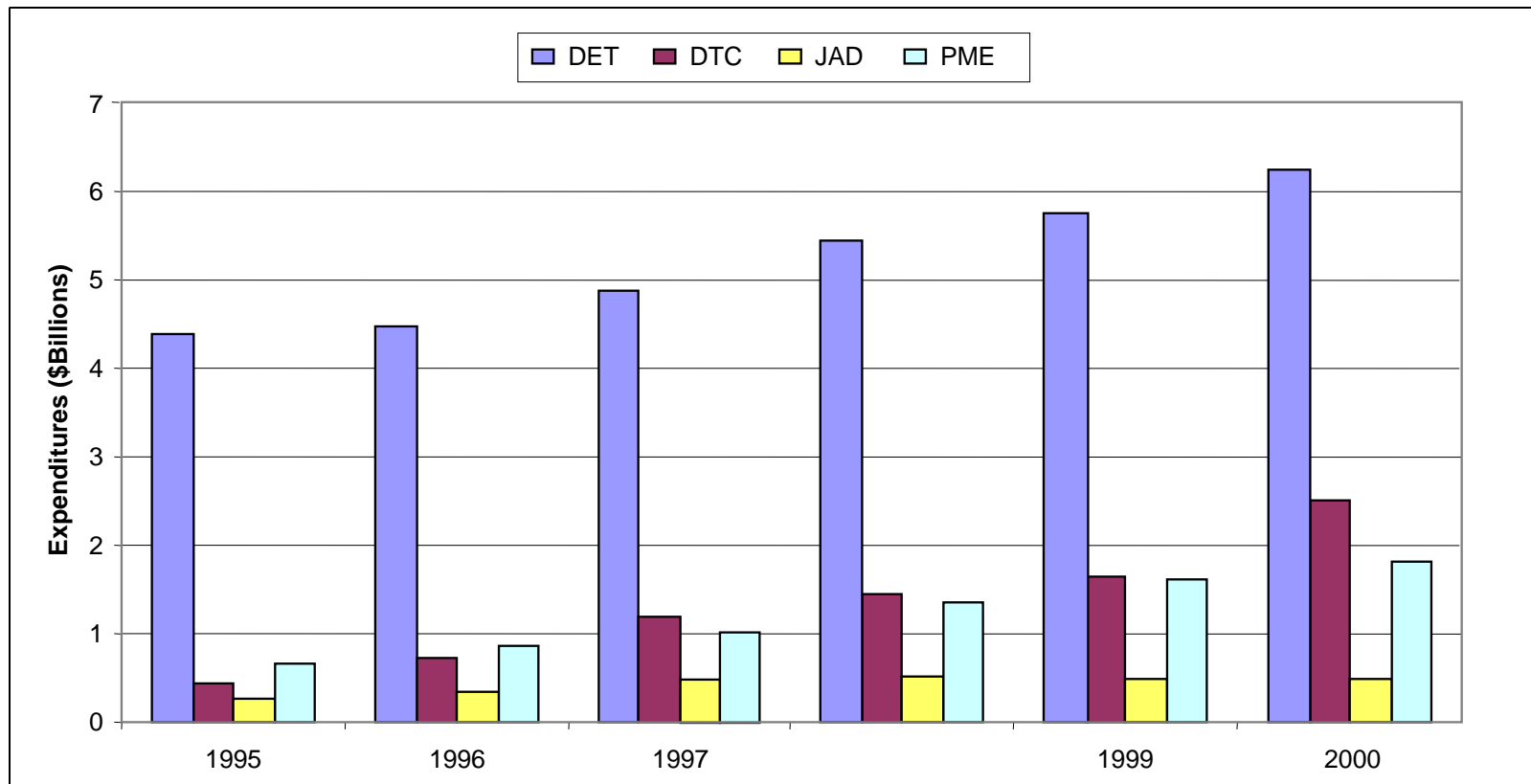
Why the Pharmaceutical Industry?

- ◆ Industry spend is ~ 10 billion
 - Largest amount spent on sales force by any industry
- ◆ Size of detailing activity
 - 600,000 physicians in the US
 - 125,000 regular prescribers
 - 80,000 detailers
 - Doubled in last 5-6 years
 - \$ 80-120 per call
- ◆ High-quality data

What is Detailing?

- ◆ Of all the marketing instruments used in the industry
 - Detailing accounts for the largest share of industry marketing expenditure
 - Seems to provide the highest return on investment
- ◆ Detailing
 - Personal communication situation between sales representative and physician
 - No actual sale takes place (strong test of hypothesis)
- ◆ Typical Detail
 - Exchange of information
 - Social interaction
 - Sample drops
 - Lasts around two minutes

Industry Marketing Expenditure



Role of Detailing

- ◆ Detailing is an important source of information (Williams & Hensel 1991, Ziegler et al 1995, Lexchin 1989)
 - However, the importance of detailing as a source has been declining
 - Most important source in the 1950-60s
 - Post 1970, it is between 4th and 7th in importance as a source
- ◆ Attitudes to detailing are mixed among physicians
 - Range from negative to neutral on technical dimensions
 - Range from neutral to positive on non-technical dimensions
 - For new products, physicians agree that detailing plays an important role in increasing awareness of a drug
 - In general, physicians do not believe that prescription behavior is influenced by detailing

A Specific Problem

Response to Sales force contact

- How is sales force effort allocated?
- What implicit knowledge of response is used in allocation?

Physician Prescription (Rx) Data

Data

Mature drug category (top three prescribed)

Drug X is share leader and under patent (1999-2001)

Data available for a Physician panel

~600,000 physicians in the US - however, only about 100,000 active regular prescribers

Monthly Rx (NRx versus TRx)

Monthly detailing visits and sampling activity

Physician specialty

Data is compiled from internal company records and IMS pharmacy audits and supplied to us by a leading Market Research company.

Current Industry Practice

Use of pooled models (pooling done on category prescription volume using decile bins). This is problematic.

Suppose:

Detailing chosen by past volume of category scripts

Implication:

Those who prescribe a lot *on average* will get detailed a lot.

Conclusion:

High volume will automatically be associated with a high *average* level of detailing even if detailing is completely ineffective

Barriers to Physician-level Modeling

Appropriate response model

Monthly Rx (esp. NRx) are discrete with zeroes

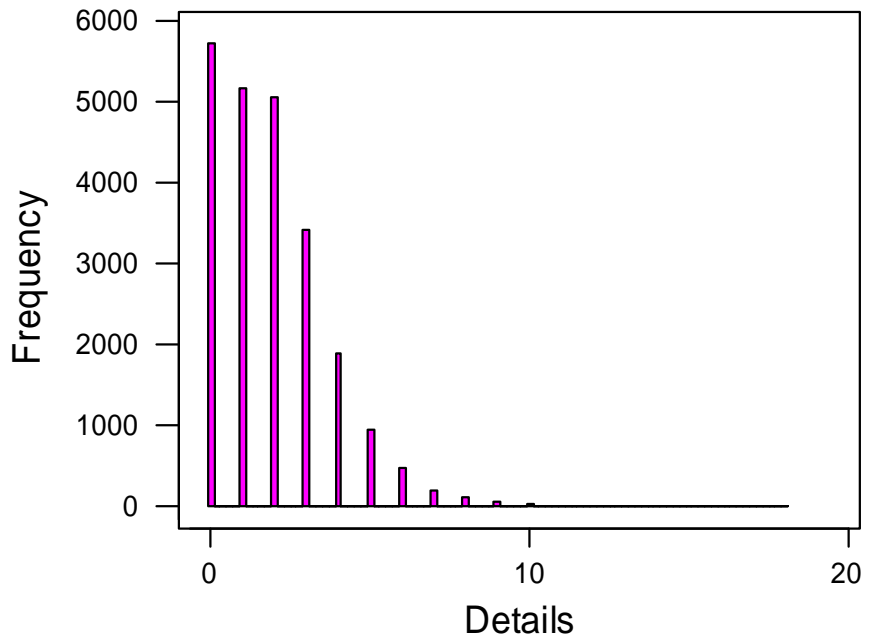
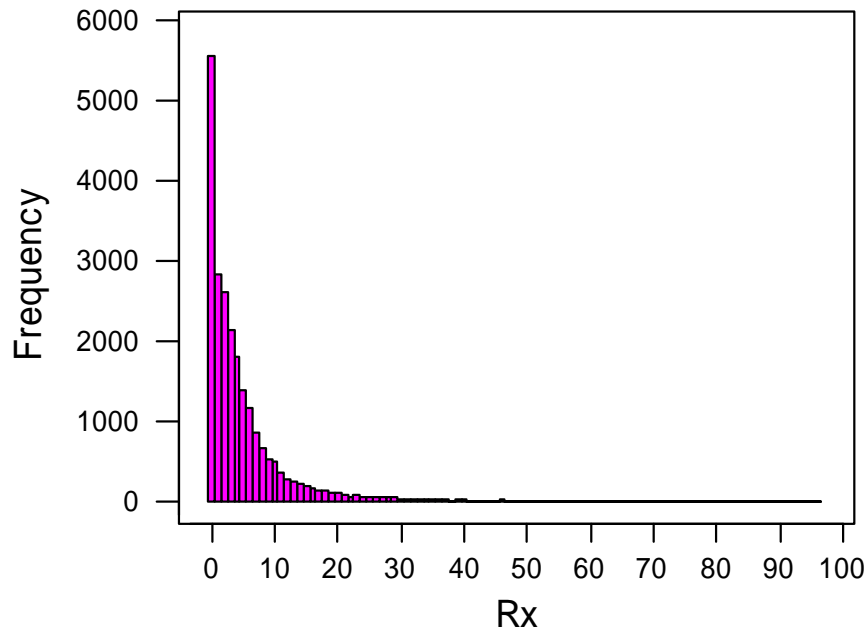
Detailing is even more discrete

Reliable Inference at Physician level

Small amount of information?

Depends on demands for model (sampling effects/carry-over/diminishing returns)

Discrete Data



Monthly data (for 24 months) for a sample of 1000 physicians

Wish list for Response Model

Allow for physician level differences in level of Rx and responsiveness to detailing

Allow effects of detailing to be felt in current and future months (carry-over effects)

Allow for systematic differences by specialty

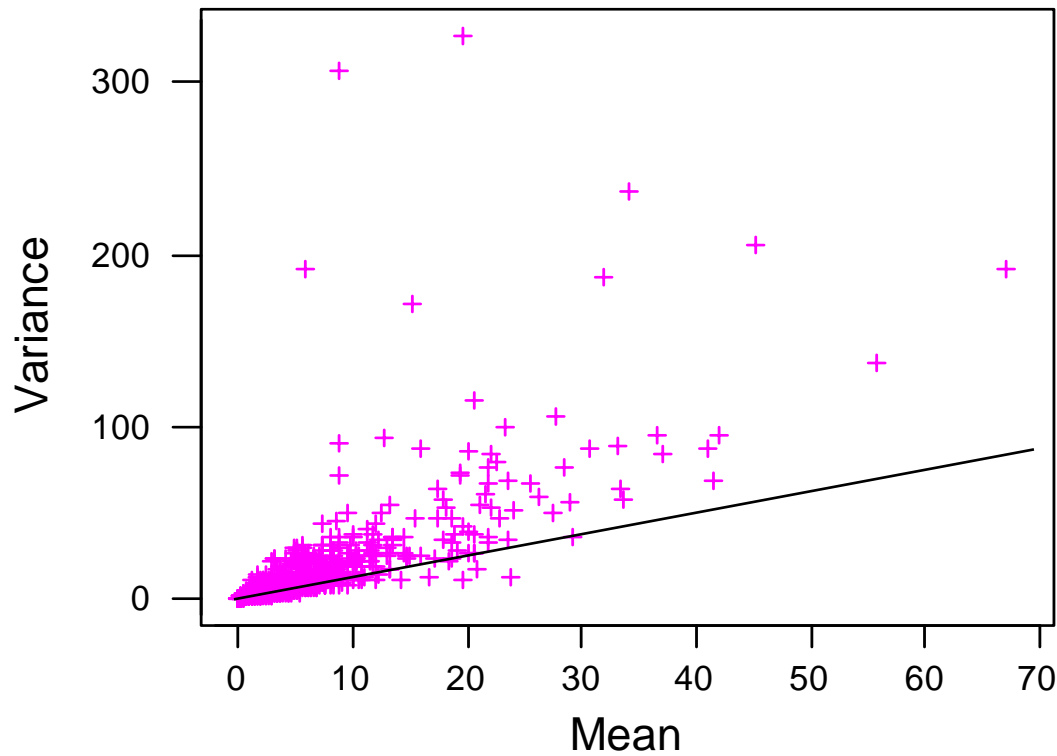
Utilize information on sampling

Allow for diminishing returns?

RAPP studies show $ROI > 1$. Implies massive underutilization of detailing. Can we detect diminishing returns on physician level?

Count Model Selection: Over-dispersion

New Prescriptions for Drug X



N=1000
T=24

Dealing with Over-Dispersion

Plot shows clear over-dispersion.

We are observing averages for each physician. This could be a mixture of Poissons over the Random Effects distribution. A mixture can be over-dispersed.

Adopt NBD specification. Additional parameter to handle over-dispersion. Poisson is limiting case. (Note, NBD can't handle under-dispersion).

NBD Regression

$$\Pr(y_{it} = k | \lambda_i) =$$

$$\frac{\Gamma(\alpha + k)}{\Gamma(\alpha)\Gamma(k + 1)} * \left(\frac{\alpha}{(\alpha + \lambda_{it})} \right)^\alpha * \left(\frac{\lambda_{it}}{(\alpha + \lambda_{it})} \right)^k$$

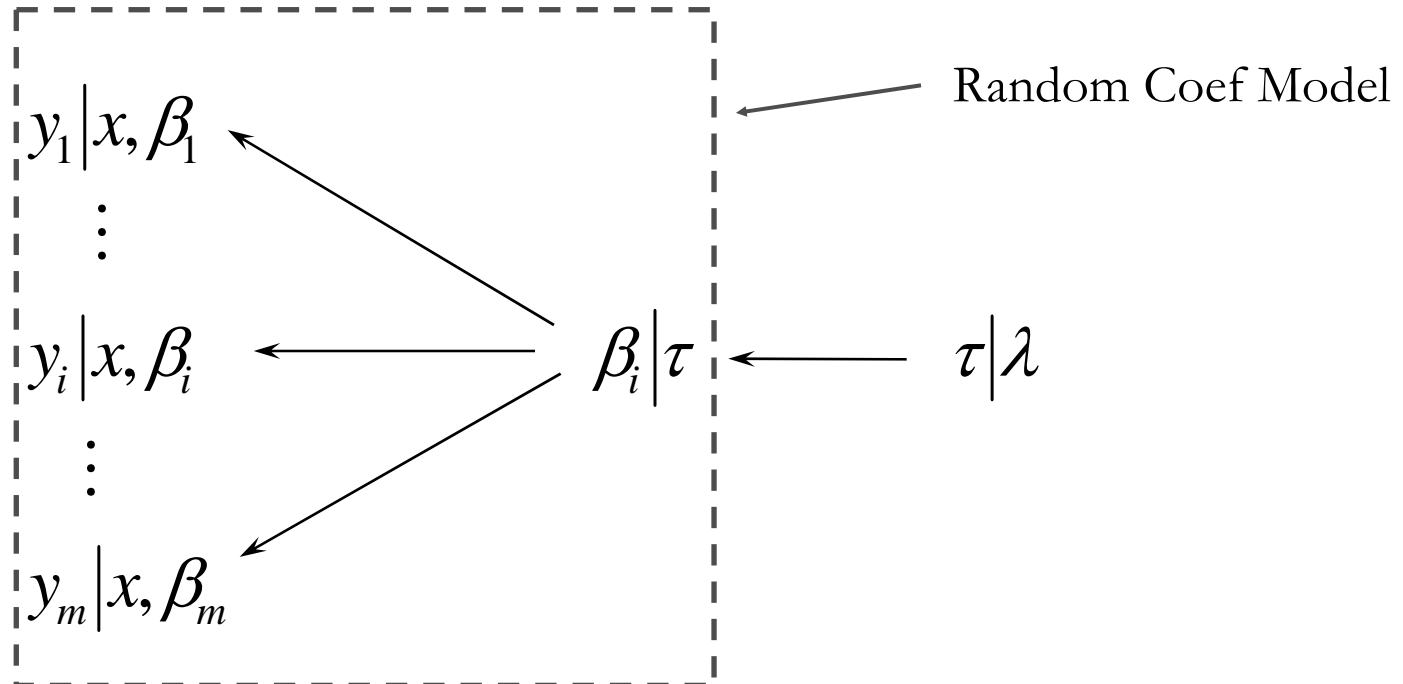
$$E[y_{it} | x_{it}] = \lambda_{it} = \exp(x_{it}' \beta_i)$$

$$\lambda_{it} = \exp(\beta_{0,i} + \beta_{1,i} Det_{it} + \beta_{2,i} \ln(y_{it-1} + 1))$$

Carry-over effect

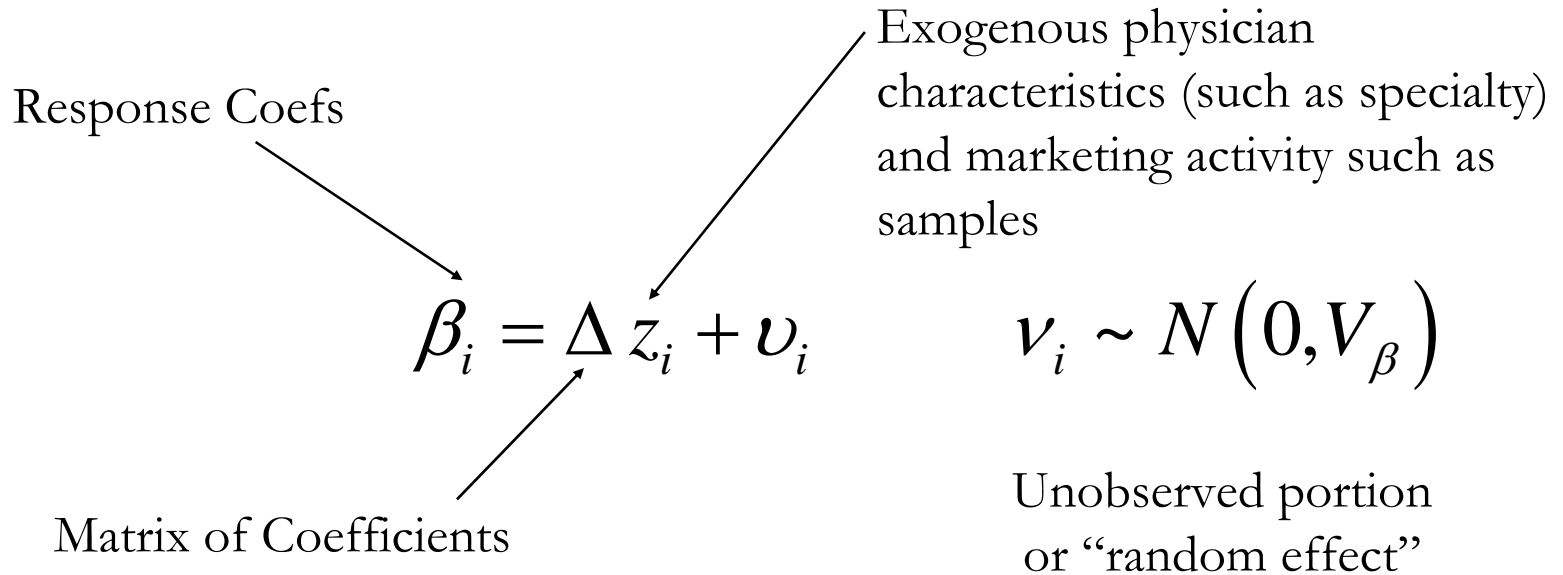
Common alpha parameter handles over-dispersion. As alpha gets large, we get back Poisson.

General Form for Hierarchical Models



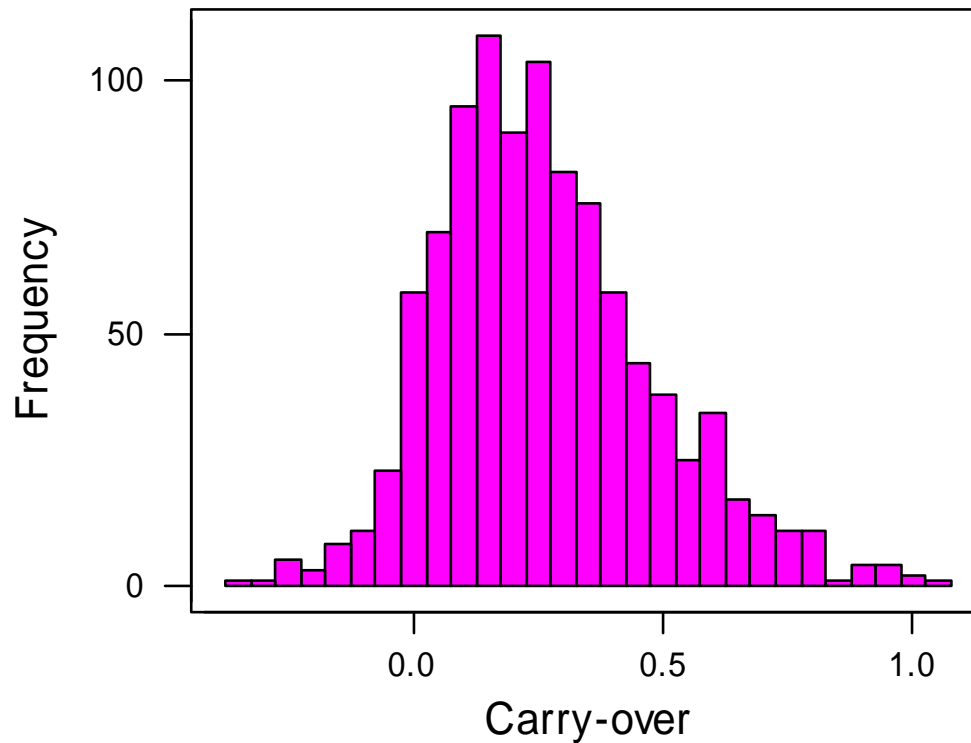
Set of parms to be “estimated”: $\{\beta_i\}, \tau$

Specific Hierarchy



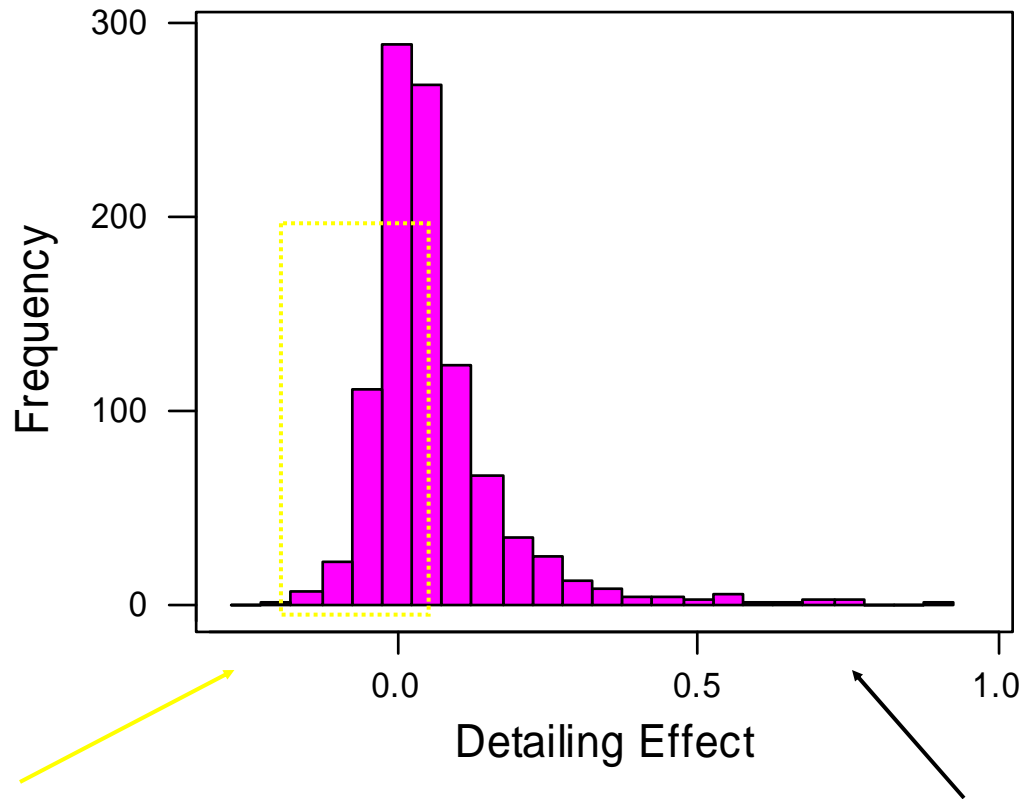
Ex: Responsiveness to detailing (one of betas) is a linear function of specialty and sampling plus normal distribution. The normal component is only revealed by scripting behavior

Results from NBD Model



Median: .28; 367 with post prob > .9

Results from NBD Model



Long-Run
Effect of an
Additional
Detail

$$\frac{\beta_{1,i}}{(1 - \beta_{2,i})}$$

Negative: 3 with post prob > .9. Positive: 47 with post prob > .9

Adding to the Conditional Model

All regression approaches take the X variables as given. This means that we are identifying the physician-level parameters from variation from month to month in detailing as well as the role of the hierarchical prior (shrinkage).

In our case, the average level of detailing is set by sales force managers (quarterly horizon). Month to month variation in this average level is a matter of execution error which we do not think is systematic.

Adding to the Conditional Model

The average level of detailing is set by informed people.

Two scenarios:

1. Level of detailing depends on volume of scripts in category, e.g. on $\beta_{0,i}$
2. Level of detailing depends on responsiveness as well, e.g. on $\beta_{0,i}$ *and* $\beta_{1,i}$

Managers use their own (possibly data-based) priors

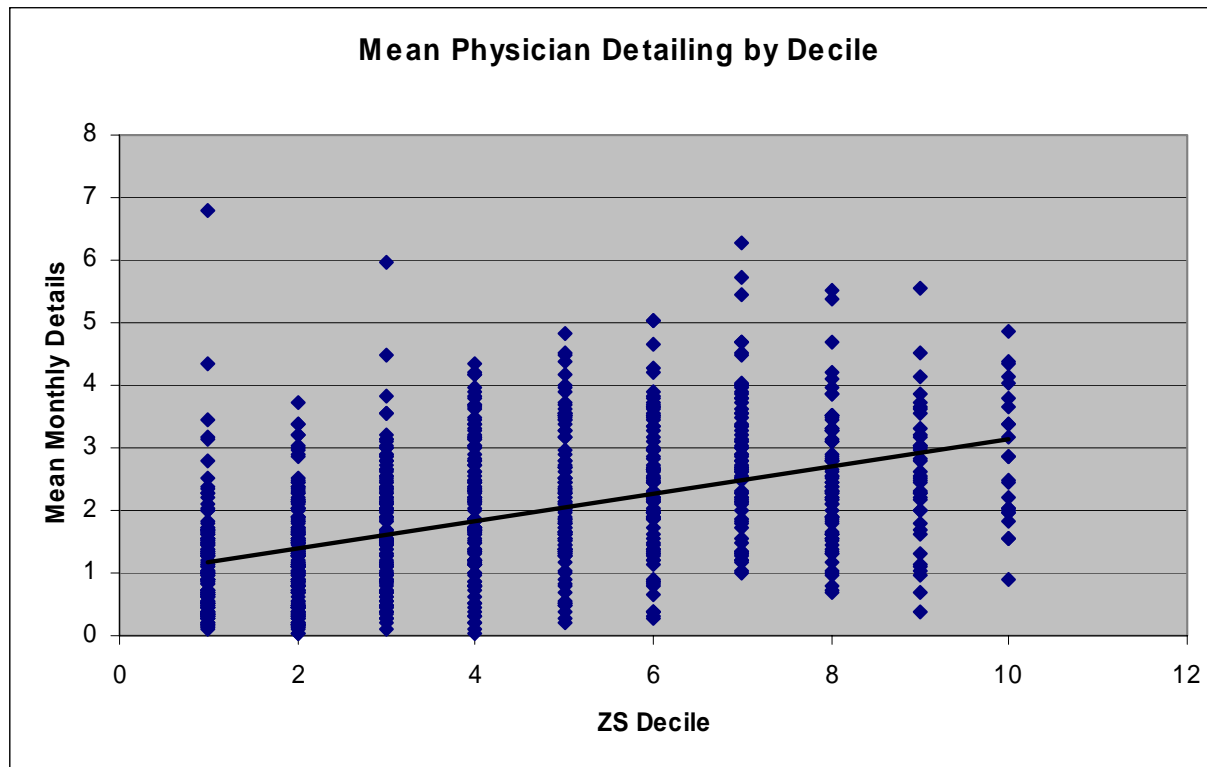
Adding to the Conditional Model

This suggests:

1. There is information in the level of detailing about the individual parms. Some one who is detailed a lot probably is more responsive or at least is a high volume writer. This level information is NOT used by conditional models
2. Estimates from conditional models can be “biased.” Chamberlain (*REStud* 1980) shows that, for a very simple model, the estimates are consistent only as T goes to infinity. Thus, predictions of response to new detailing policies will be systematically wrong.

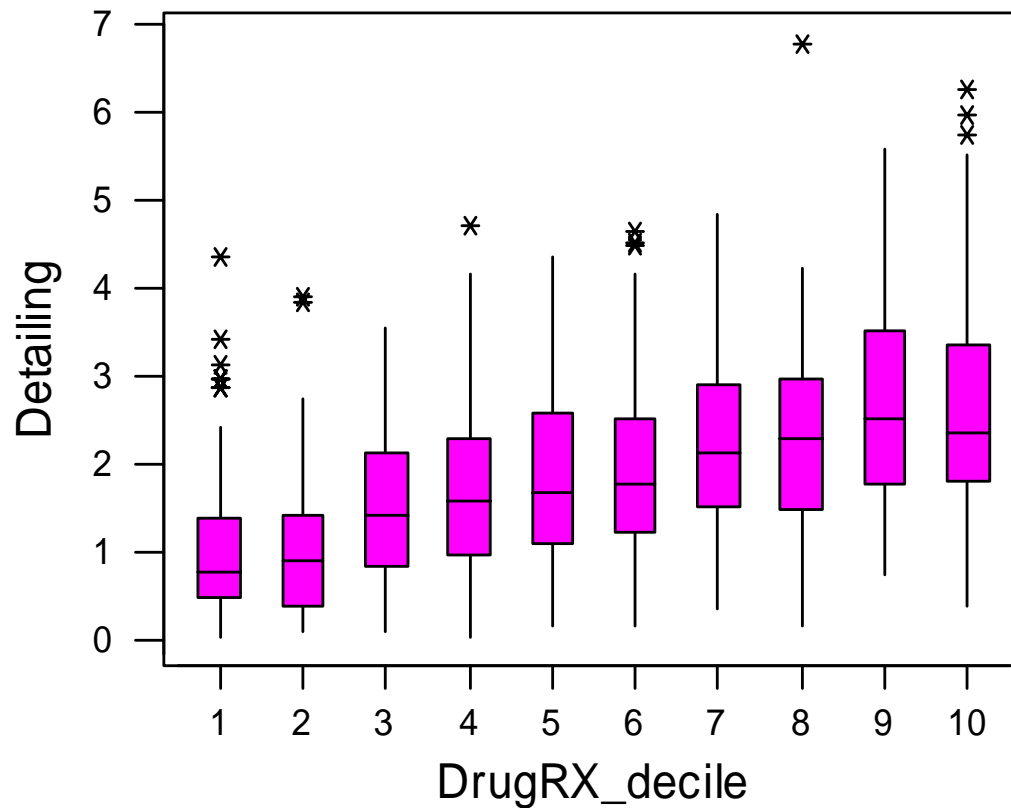
Current Detailing Policy

Physicians divided into deciles based on category volume,
level of detailing based on decile



Current Detailing Policy: Further Evidence

Detailing by mean drug NRx



Adding to the Conditional Model

We have to add more structure. We must include not only a model of the conditional distribution of scripts given detailing but also of the marginal distribution of detailing

$$y_{it} | x_{it}, \beta_i, \alpha$$

NBD Regression

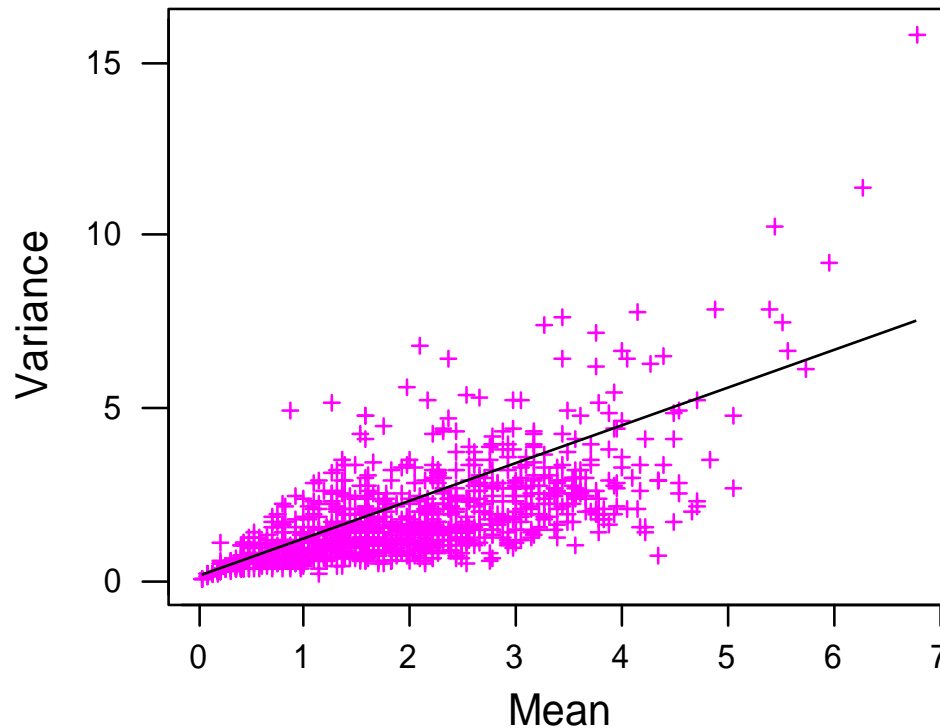
$$x_{it} | \beta_i, \gamma$$

Marginal on Detailing

Note dependence on beta!

Marginal Distribution of Detailing

What is the appropriate distribution? Check for over-dispersion as before (data for 1000 physicians).



Poisson looks OK.

Marginal Distribution of Detailing

$$\Pr(x_{it} = m \mid \mu_i) = \frac{\mu_i^m \exp(-\mu_i)}{m!}$$

$$\mu_i = \exp \left\{ \gamma_0 + \gamma_1 \left[\frac{\beta_{0i}}{(1 - \beta_{2,i})} \right] + \gamma_2 \left[\frac{\beta_{1i}}{(1 - \beta_{2,i})} \right] \right\}$$

Here we view detailing levels as iid Poisson with a mean that is related to the individual level coefficients. (Note that average autocorrelation of detailing < .3).

We will let the data tell us what the sales managers are using to set the level of detailing.

“Full” Model Conditional Likelihood

$$\prod_i \prod_t p_{NBD} (y_{it} | x_{it}, \beta_i, \alpha) p_{poisson} (x_{it} | \mu_i)$$

or

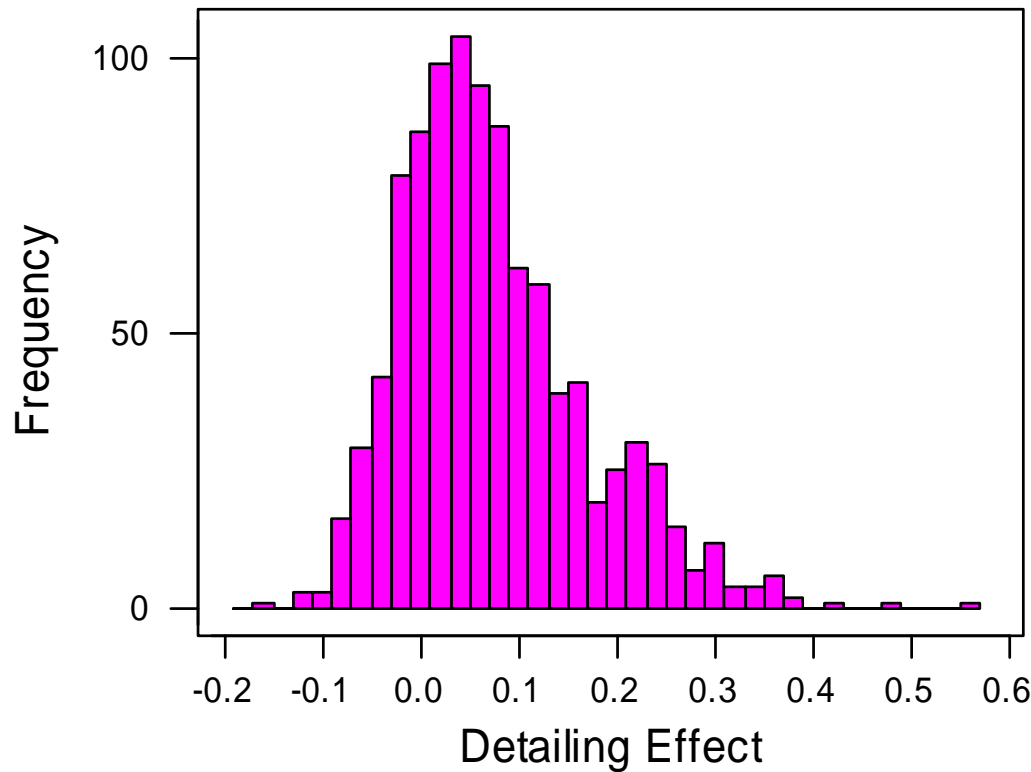
$$\mu_i = \gamma' \beta_i$$

$$\prod_{i,t} p_{NBD} (y_{it} | x_{it}, \beta_i, \alpha) \prod_{i,t} p_{poisson} (x_{it} | \mu_i)$$

NBD: uses time-series variation within and across physicians to estimate beta

Poisson: pools across all betas to infer mean detailing “policy”

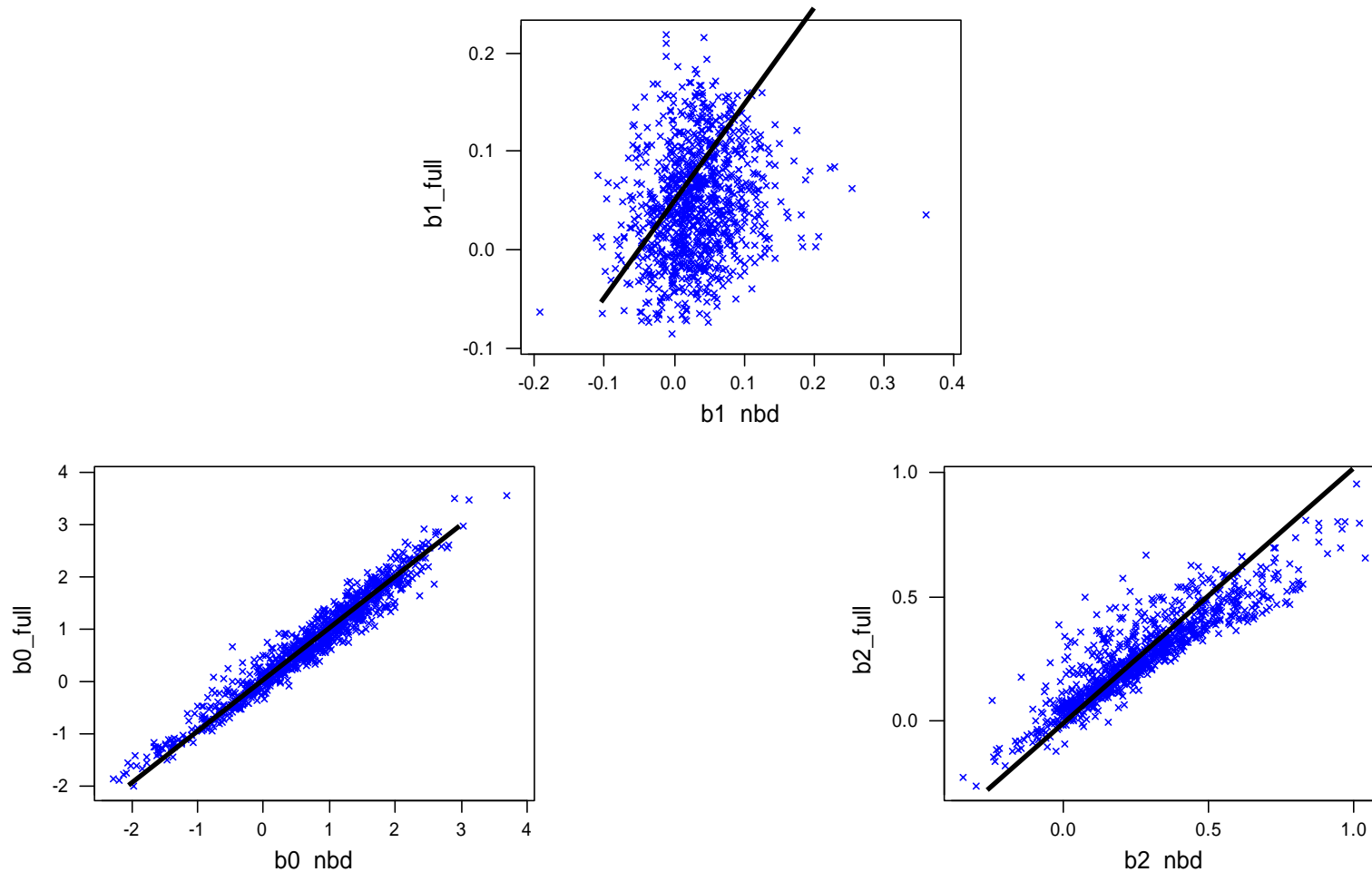
Results from “Full” Model: $Y | X$ plus X



549 (47) Positive with post prob > .9

88 (3) negative with post prob > .9

Full and Conditional Model Comparison



Hierarchical Mean Functions

$$\mu_{\beta_{0,i}} = \delta_{01} + \delta_{02} \textit{Specialist} + \delta_{03} \textit{Other} + \delta_{04} \textit{Samples}$$

$$\mu_{\beta_{1,i}} = \delta_{11} + \delta_{12} \textit{Specialist} + \delta_{13} \textit{Other} + \delta_{14} \textit{Samples}$$

$$\mu_{\beta_{2,i}} = \delta_{21} + \delta_{22} \textit{Specialist} + \delta_{23} \textit{Other} + \delta_{24} \textit{Samples}$$

Specialists write more scripts for drug and are more responsive to detailing, exhibit larger carry-over

Sampling increases volume of scripts but negative interaction with detailing

Results from “Full” Model: Y | X plus X

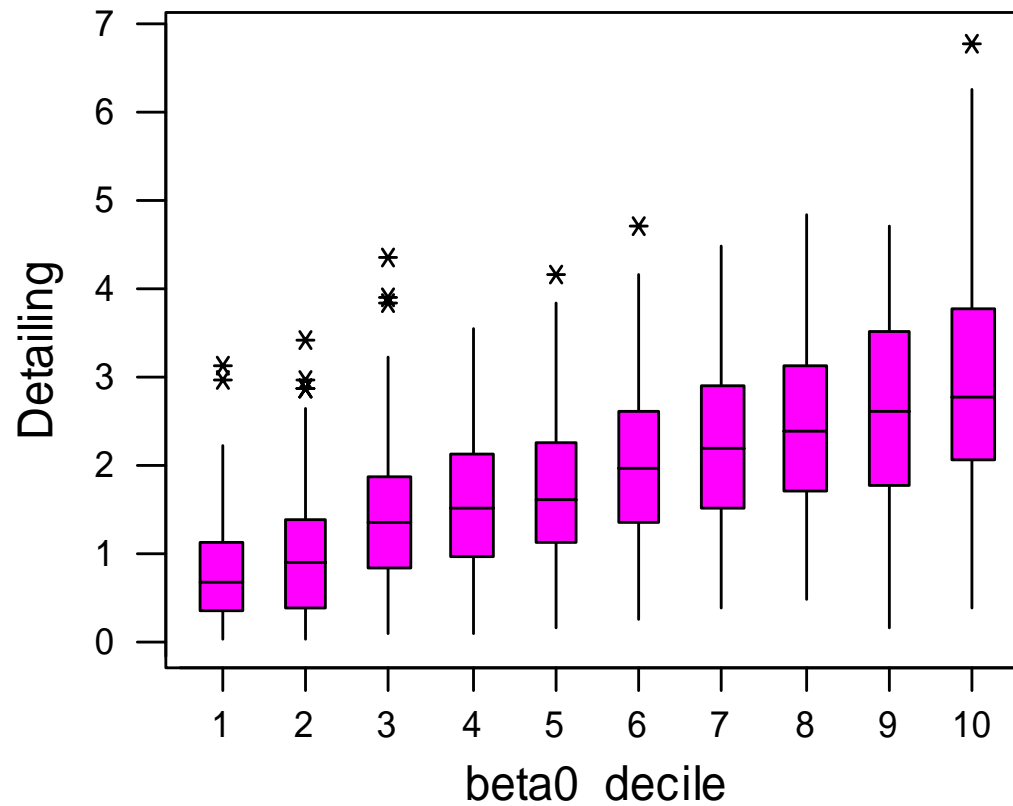
$$X_{it} \sim \text{Poisson}(\mu_i = \ln(\gamma' \beta_i))$$

$$\ln \mu_i = \gamma_0 + \gamma_1 \left[\frac{\beta_{0i}}{(1 - \beta_{2,i})} \right] + \gamma_2 \left[\frac{\beta_{1i}}{(1 - \beta_{2,i})} \right]$$

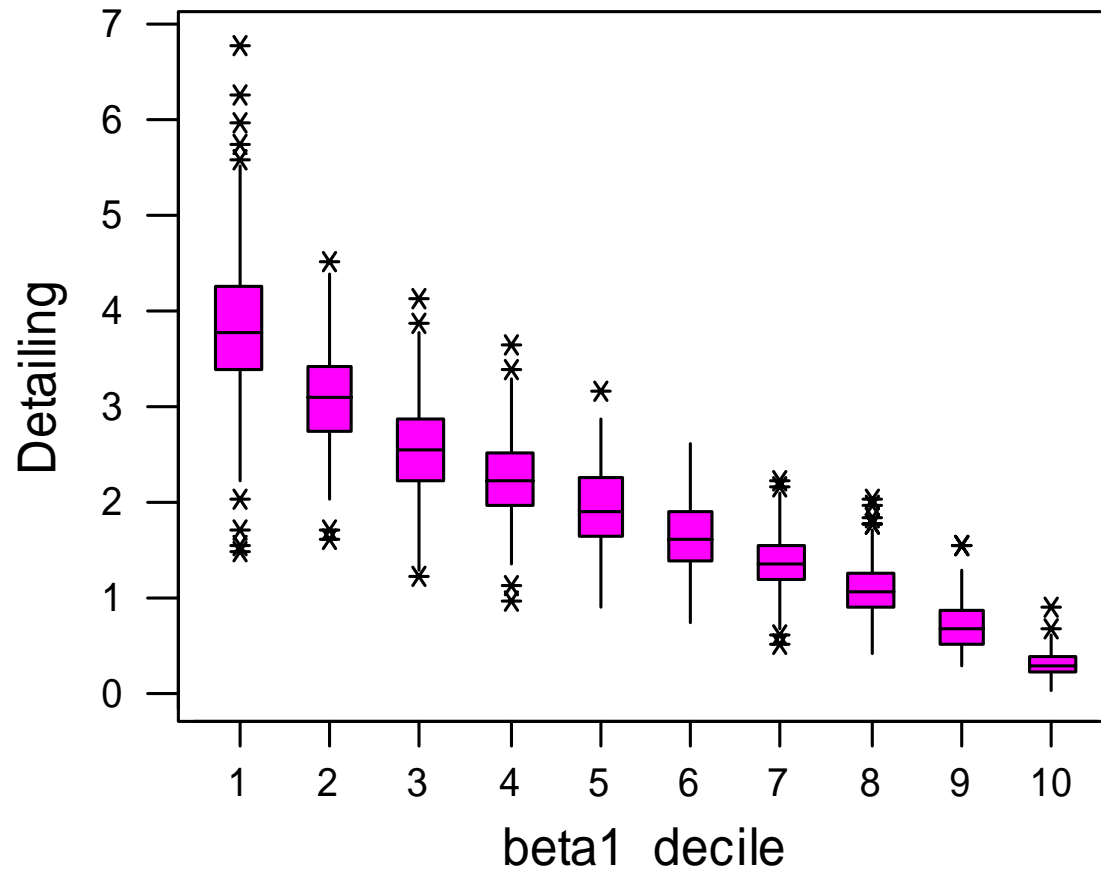
$$E[\gamma_1] = .19 \quad \text{Std}(\gamma_1) = .04$$

$$E[\gamma_2] = -6.1 \quad \text{Std}(\gamma_2) = .35$$

Interpreting Gamma Parameters



Interpreting Gamma Parameters



Unexpected finding...

Could this finding be generated by our model structure?
Check using standard conditional model.

Role of competitive detailing

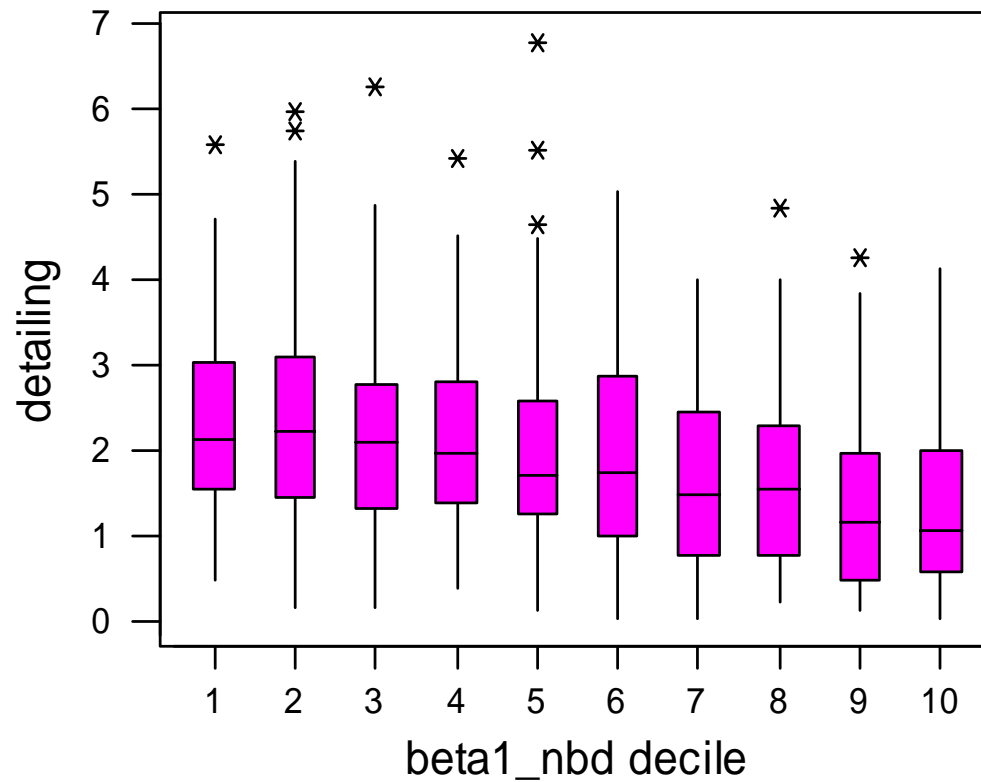
Everybody goes after same physician thus lowering effectiveness of detailing. One possible mechanism is lack of access to physician.

Use rule other than volume/responsiveness to set detailing

Data based – Share of drug X, Share of competitive drug,.....

“Non-data” based - Opinion leaders,.....

Detailing-Responsiveness: Conditional Model



Is All this Horsepower Worth It?

Within sample (holdout last two observations for each physician).

12% reduction in MSE relative to conditional model.

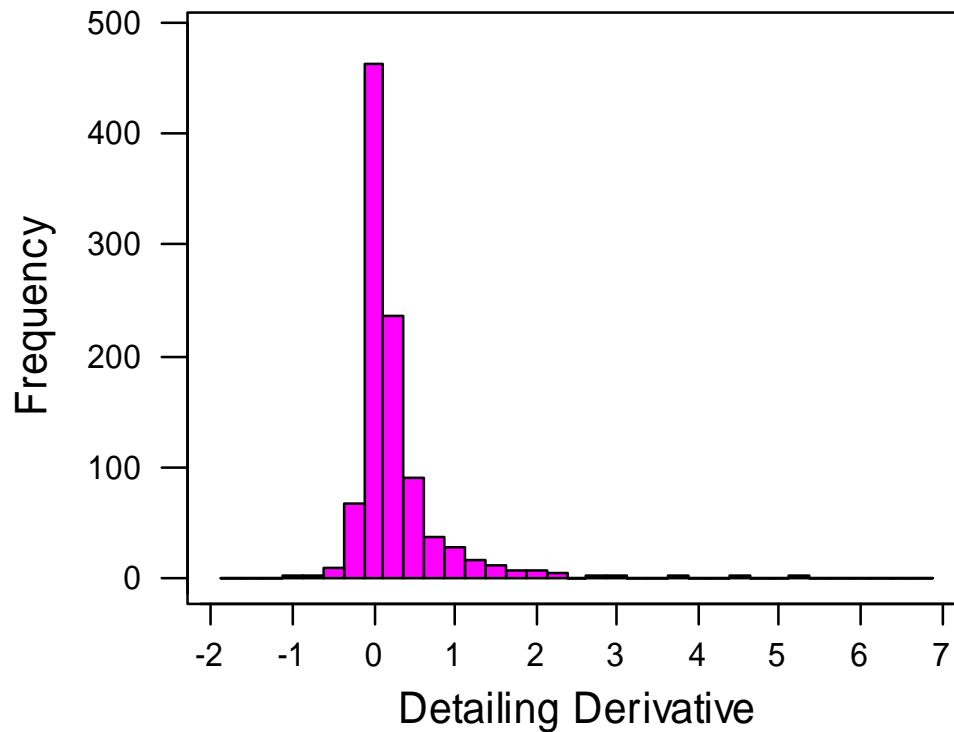
Out of sample (draw random sample of new 1000 physicians).

Use two rules – use observed detailing to decide “beta” and/or use gammas to compute constrained “beta”

4-6% reduction in MSE relative to conditional model.

So model seems to reduce bias in individual parameters (note increase in total parameters is insignificant – 3000 to 3003)

So What are the Implications?



Detailing derivatives

$$\frac{\partial E[y]}{\partial Det} = e^{\ln \mu^*} \beta_{1,i} / (1 - \beta_{2i})$$

Detailing Derivatives ...

Many derivatives are “small.” What is their economic significance?

Evidence for/against optimality?

Optimality metric: $MR = MC$

$MR = \text{Expected Increase New Rx} * \text{Margin per Rx} * \text{Expected Lifetime Rx}$

$MC = \$80$

Assumption of optimality implies how many lifetime scripts?

Detailing Derivatives ...

For Optimality-

Median Derivative implies \$296 lifetime rev or 3 scripts
at @\$100 net margin

25 Percentile implies \$917 lifetime rev or > 9.2 scripts

75 Percentile implies \$50 lifetime rev or .5 scripts

So glass is half-full or half-empty

Over/under detailing for about 50 per cent of physicians.

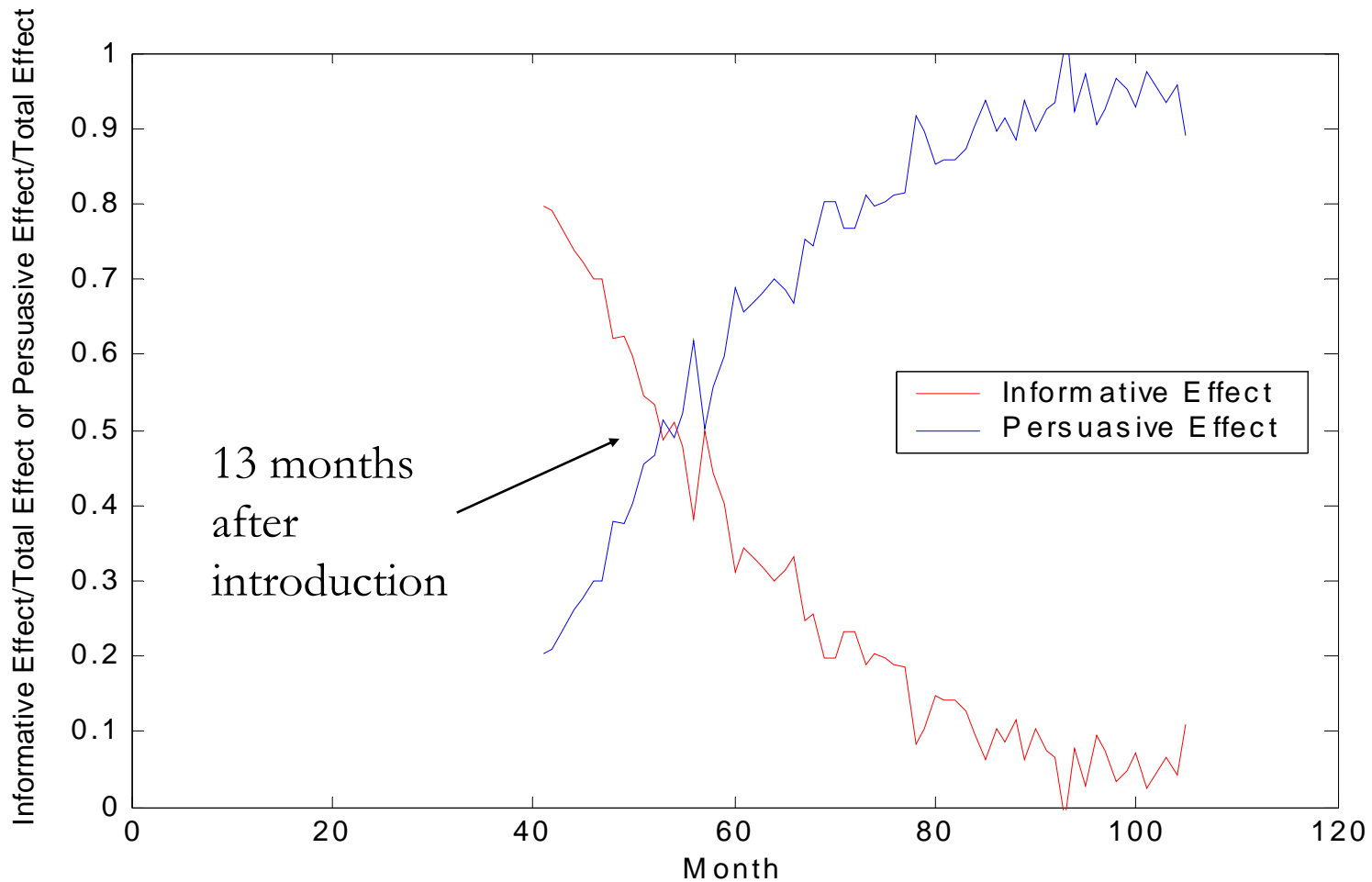
Why does Detailing Matter: Narayanan et al 2002

- ◆ Role of Advertising
 - Informative Role: informs about true attribute/quality and reduces uncertainty
 - Persuasive Role: affects utility directly (and is *not* informative)
 - Different roles for new and familiar products
- ◆ Thus, our main research question was
 - Can we find evidence for these two roles of detailing?
 - If yes, we should see a change in the relative proportion of these two roles over the product life cycle: Informative first, then Persuasive
- ◆ 2nd generation Antihistamine category: 3 drugs, data from inception, 10 years of monthly observations

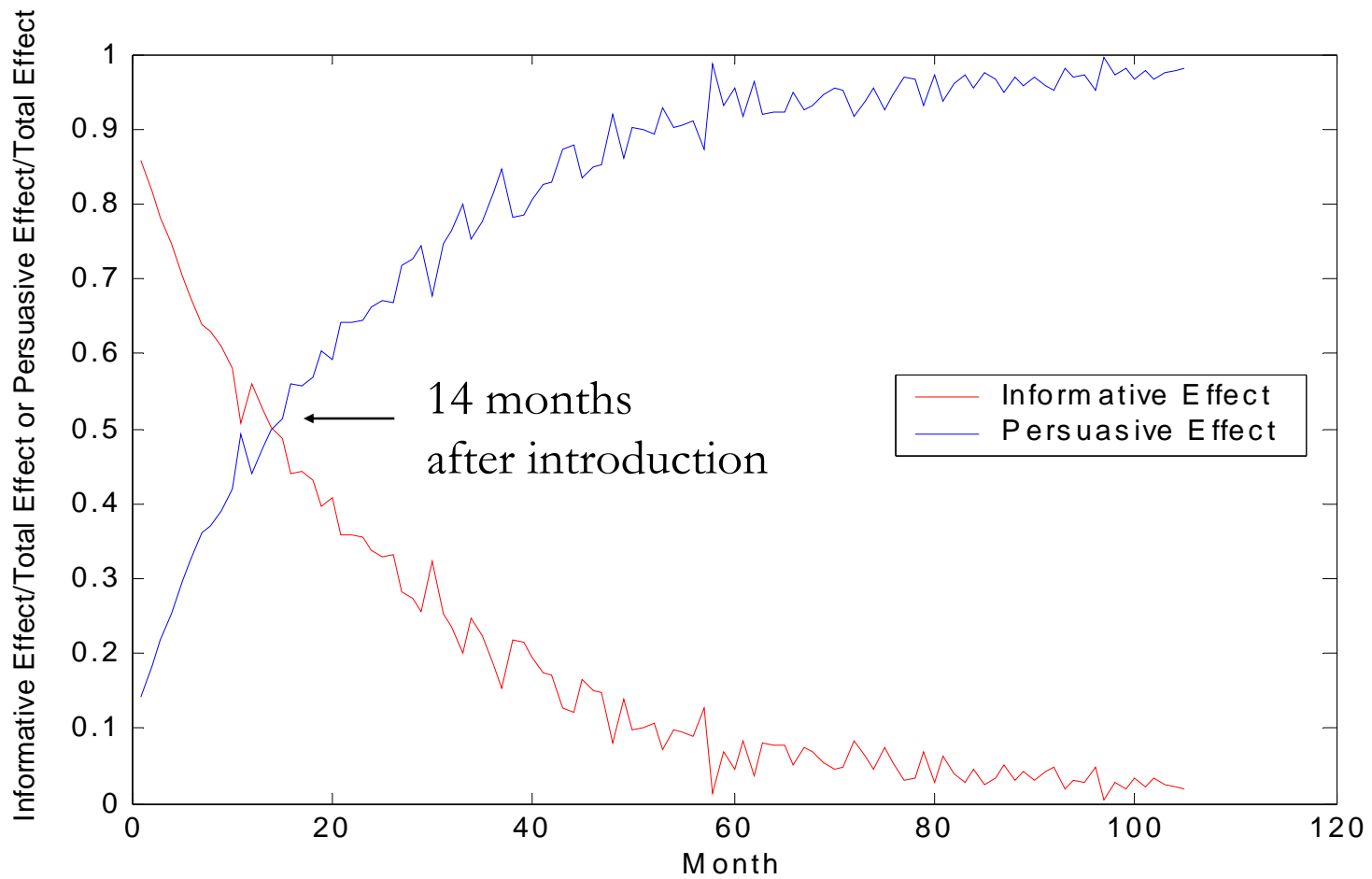
Why does Detailing Matter: Narayanan et al 2002

- ◆ Model assumes that physicians value patient health and are uncertain about the efficacy of the drugs
- ◆ Model also assumes that physicians learn about this efficacy
 - Via a Bayesian learning process
 - Both prescription experience and marketing variables enable learning
- ◆ Main findings
 - Detailing reduces uncertainty about efficacy in early stages of product life
 - However, this role of detailing dominates only for a short period post-launch (6-14 months)
 - “Relationship” building role of detailing takes over after this period and is the larger role over the life cycle

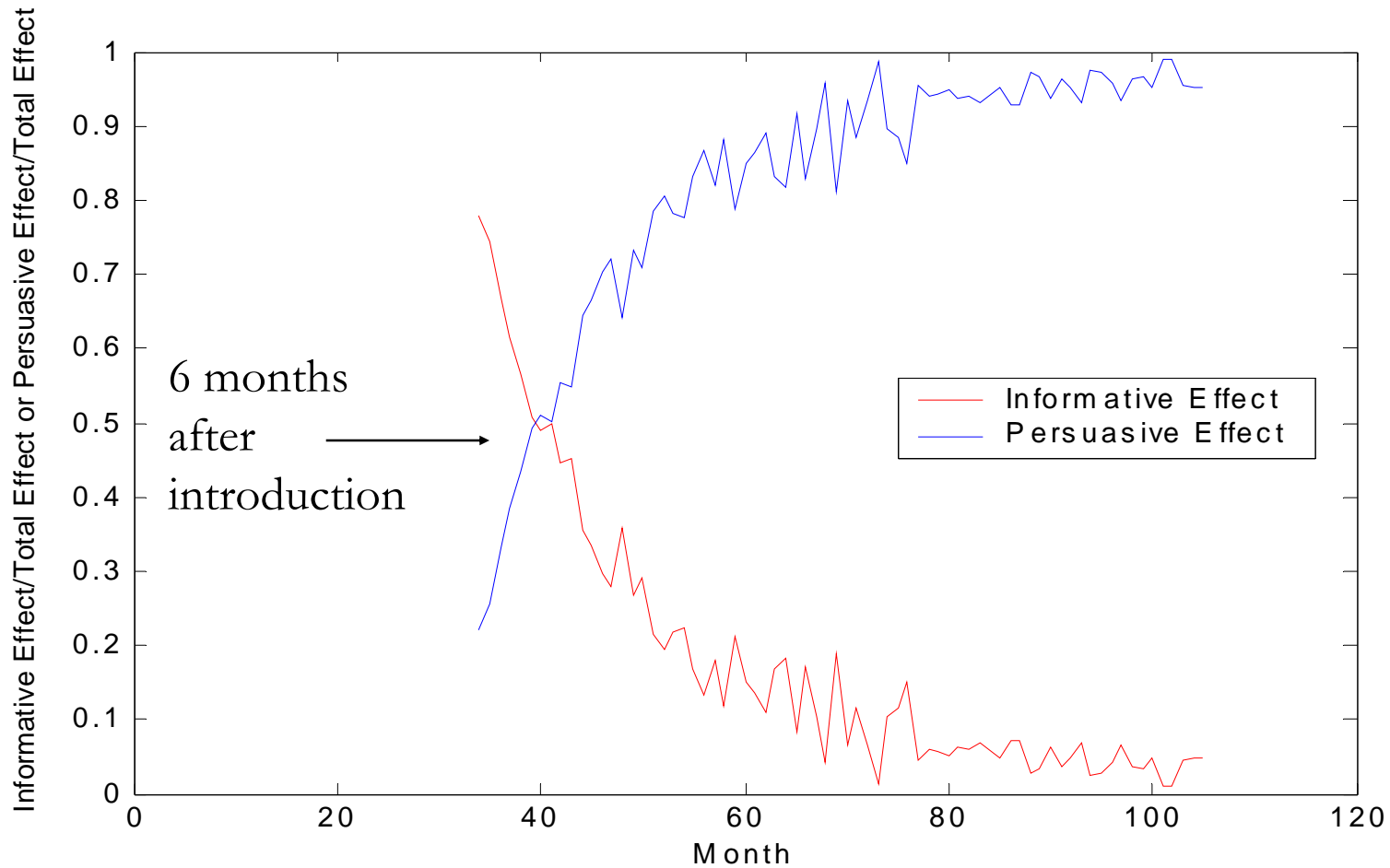
Role of Detailing - Allegra



Role of Detailing – Proportions (Claritin)



Role of Detailing - Zyrtec



Conclusion

Models that look at of individual customers provide detailing insights about response to sales force effort. In other words, the more disaggregate, the better.

To do this correctly using data, it is important to model how sales force effort is allocated.

The right metric to look at is the relationship between individual level Marginal Revenue and Marginal Cost. This can help design optimal sales force allocation plans.

Our approach can potentially be applied to any marketing instrument and industry.

Implementation issues?

Papers and References

◆ Available at

<http://gsb.uchicago.edu/fac/puneet.manchanda/research>